

Deep neural network for maximizing output power estimation of dual-axis solar tracker

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Article Info

Article history:

Received Jul 29, 2024

Revised Dec 5, 2024

Accepted Jan 27, 2025

Keywords:

Artificial neural network

Deep learning

Output power

Prediction

Solar tracker

ABSTRACT

The abundance of solar energy sources has encouraged many researchers to maximize solar photovoltaic (PV) output power using dual-axis solar tracking. However, environmental conditions, time of day, and the angle of movement of the solar tracker can affect the resulting power output. This study aims to predict the power output of dual-axis solar tracking in order to maintain the power's stability and quality. Deep neural networks (DNN) with variations of 5 and 6 hidden layers have been proposed. The dataset used in this study was obtained from observation results and then divided into 80% training data and 20% testing data. A series of algorithms are used to recognize relationship patterns between input and hidden layers, between hidden layers, as well as hidden layers and output. Statistical results show that DNN with a variation of 6 hidden layers is better at estimating solar tracking power output with a mean absolute percentage error (MAPE) value of 12.328%, mean square error (MSE) of 0.332, and mean absolute error (MAE) of 0.425. This study can be used as a reference in utilizing artificial intelligence to predict the output power of solar panels as a renewable energy source.

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1. INTRODUCTION

Solar resources are a renewable energy source that is abundant, easy to utilize, and environmentally friendly [1]. The availability of solar energy sources is still being determined due to changes in the sun's position, so the solar cells' output power is not optimal. Increasing the output power of solar panels can be done with static systems with fixed angles [2] and single-axis [3]–[5] or dual-axis [6]–[9] solar trackers. The most effective way to increase solar cell energy is to use dual-axis solar tracking by 25.5% while single-axis is only 16.5% compared to a fixed system [10]. Environmental conditions also affect the power output produced, such as the intensity of solar radiation and environmental temperature. When the weather is cloudy, the radiation intensity will decrease, and the temperature will be low, reducing the required electricity supply [11]. The main thing that must be done is to predict the output power of solar cells [12] to maintain the stability and quality of the power produced [1].

Research related to forecasting photovoltaic (PV) output power based on computational intelligence algorithms has been widely carried out; several researchers use the artificial neural network (ANN) method to predict current solar radiation, short-term and long-term predictions [13], ANN with input namely meteorological conditions, climate, and radiometric, including wind speed and relative humidity as well as output in the form of local solar panel energy output [14], input in the form of weather conditions and PV

module characteristics [15], input in the form of environmental factors such as irradiance (G), temperature (T), humidity (H), wind speed (W) [11], input based on environmental factors [16]. Feed-forward back propagation neural network (FBANN) [17]. Support vector machine (SVM) [18], long short-term memory (LSTM) [19], support vector machine regression (SVMR) [20], recurrent neural network (RNN) [21], fuzzy regression (FR) [22], particle swarm optimization (PSO-Fuzzy) [1], and PSO-adaptive neuro fuzzy inference system (ANFIS) [23]. Among the computational methodologies used, ANN is a superior method in predicting solar cell power output compared to fuzzy logic [24] and multiple linear regression [25]. Based on this explanation, ANN is considered more effective in predicting the output power of solar panels. However, no research has predicted the power output of dual-axis solar tracking using a deep neural network (DNN) with input parameters of time, tilt angle, solar radiation intensity and environmental temperature. This paper analyses the impact of hidden layers variation in DNN model to reach the best performance based on historical data.

DNN have shown remarkable capabilities in various tasks, including perception-related ones such as image and speech recognition [26]. These models can learn increasingly abstract, higher-level representations of the input data, and have been successfully applied to medicine and health care [27]. One of the critical architectural advantages of deep learning is the use of many hidden neurons and layers, typically more than two, which allows for extensive coverage of the raw data at hand [28]. Nevertheless, the determination of the optimal number of hidden layers is a crucial aspect in the design of DNN models, as it directly impacts their performance and generalization capabilities.

2. METHOD

2.1. Architecture of deep neural network

The method applied in this paper to predict the output power of a dual-axis solar tracker is an ANN with many hidden layers, also called a DNN. There is a training process carried out to produce the desired output. The training process uses a series of algorithms to recognize relationship patterns between input and hidden layers as in (1), hidden layer 1 to the next hidden layer as in (2), and hidden layer to output as in (3) [29]. In the final stage, the neuron applies a transfer function to obtain output [14]. Therefore, the performance of DNN depends on the work of neurons [11]. The developed DNN architecture is shown in Figure 1.

$$\bar{h}_1 = \Phi(W_1^T \bar{x}) \quad (1)$$

$$\bar{h}_{p+1} = \Phi(W_{p+1}^T \bar{h}_p) \quad \forall p \in \{1 \dots k-1\} \quad (2)$$

$$\bar{y} = \Phi(W_{k+1}^T \bar{h}_k) \quad (3)$$

Where $\bar{h}_1$ is the first hidden layer, W is the weight, Φ is the activation function, and $\bar{y}$ is the output.

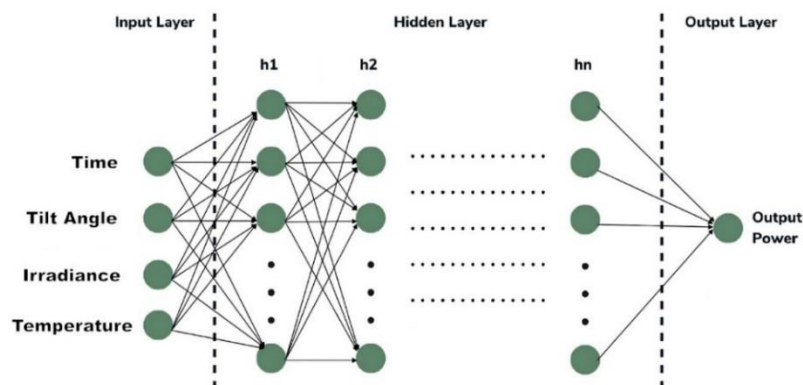


Figure 1. Architecture of DNN

The activation function functions to receive and send signals between layers [15]. Several activation functions are often used, namely Tanh, Linear, and rectified linear unit (ReLU), but the ReLu activation function provides the best results among the two [14]. Determining the number of neurons in the hidden layer

is based on trial and error, because there is no mathematical equation that can determine the number of neurons in a layer [15].

2.2. Data collection

The dataset used in this research was obtained from observations made from 08.30 to 16.30. Time parameters are divided into two categories, namely am and pm. Temperature (°C) is the environmental temperature measured during observations as well as the radiation parameter (W/m²). Meanwhile, the tilt angle (°) is the angle of movement of the solar tracking which is measured at a certain time during the observation [30]. Before the training process, the dataset is divided into 80% training data and 20% testing data. The algorithm will take data periodically from all datasets in the training process using the Adamax optimizer with 100 epochs.

2.3. Test performance of model

Mean square error (MSE) is used to measure the average squared error to minimize the error as in (4) [31].

$$MSE = \frac{1}{n} \sum_{i=1}^n (y - \bar{y}_i)^2 \quad (4)$$

With y is actual data and n representing the total number of samples. The mean absolute error (MAE) is the average of the absolute error value of actual data and the predicted value as in (5) [31].

$$MAE = \frac{1}{n} \sum_{i=1}^n |y - \bar{y}_i| \quad (5)$$

Mean absolute percentage error (MAPE) aims to measure the level of model accuracy by calculating the absolute difference between actual data and predicted values, then dividing it by the actual value, then multiplying by 100 to express it as a percentage as in (6) [31].

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y - \bar{y}_i}{y} \right| \times 100 \quad (6)$$

3. RESULTS AND DISCUSSION

The main objective of this research is to develop a DNN model by comparing 5 hidden layers, and 6 hidden layers to predict the output power of a dual-axis solar tracker with the input parameters of time, tilt angle, solar radiation intensity, and environmental temperature. Table 1 shows the performance of the DNN model used with various hidden layers in the training and testing process. Based on Table 1, it can be seen that both predictors track actual data and can be used for estimation, but the DNN model with 6 hidden layers have the best performance compared to 5 hidden layers. The best performance is the DNN model with 5 hidden layers at the 95th epoch with a loss (MSE) of around 0.9626 and 0.3213 for 6 hidden layers at the 89th epoch. This is because each layer builds on the features extracted by the previous layer, allowing the model to understand and represent complex patterns and structures in the data.

Table 1. Performa DNN model with a variety of hidden layer

Hidden layers	Training			Testing		
	MAPE (%)	MSE	MAE	MAPE (%)	MSE	MAE
5	33.228	1.309	0.891	42.553	1.001	0.776
6	19.417	0.595	0.586	12.328	0.332	0.425

The performance of the model developed in the training and testing process is shown in Figure 2, with matrix performance in Figures 2(a) to 2(f). Meanwhile, the comparison of actual data with predicted data for the two models is shown in Figure 3, with 5 hidden layers in Figure 3(a) and 6 hidden layers in Figure 3(b). The results clearly show that the DNN algorithm may be used to estimate the output power of PV modules. The following provides a succinct and understandable summary of the outcomes of trained DNN mapping predictors to continuous responses. It is important to highlight from the above results that testing and validity dates were not conducted on the training dataset.

From the Figure 3, we can see that there is still a significant inaccuracy in predicting the output power of the solar tracker on the 1st, 6th, 7th, 19th, and 21st test data using DNN with 5 hidden layers; the resulting prediction results are lower than the actual data. Otherwise, on the 3rd, 11th, and 14th test data, the

DNN model with 5 hidden layers predicts higher results than the actual data. Meanwhile, the performance of the DNN model with 6 hidden layers can better predict the solar tracker's output power. This is because the more hidden layers can produce higher accuracy [15].

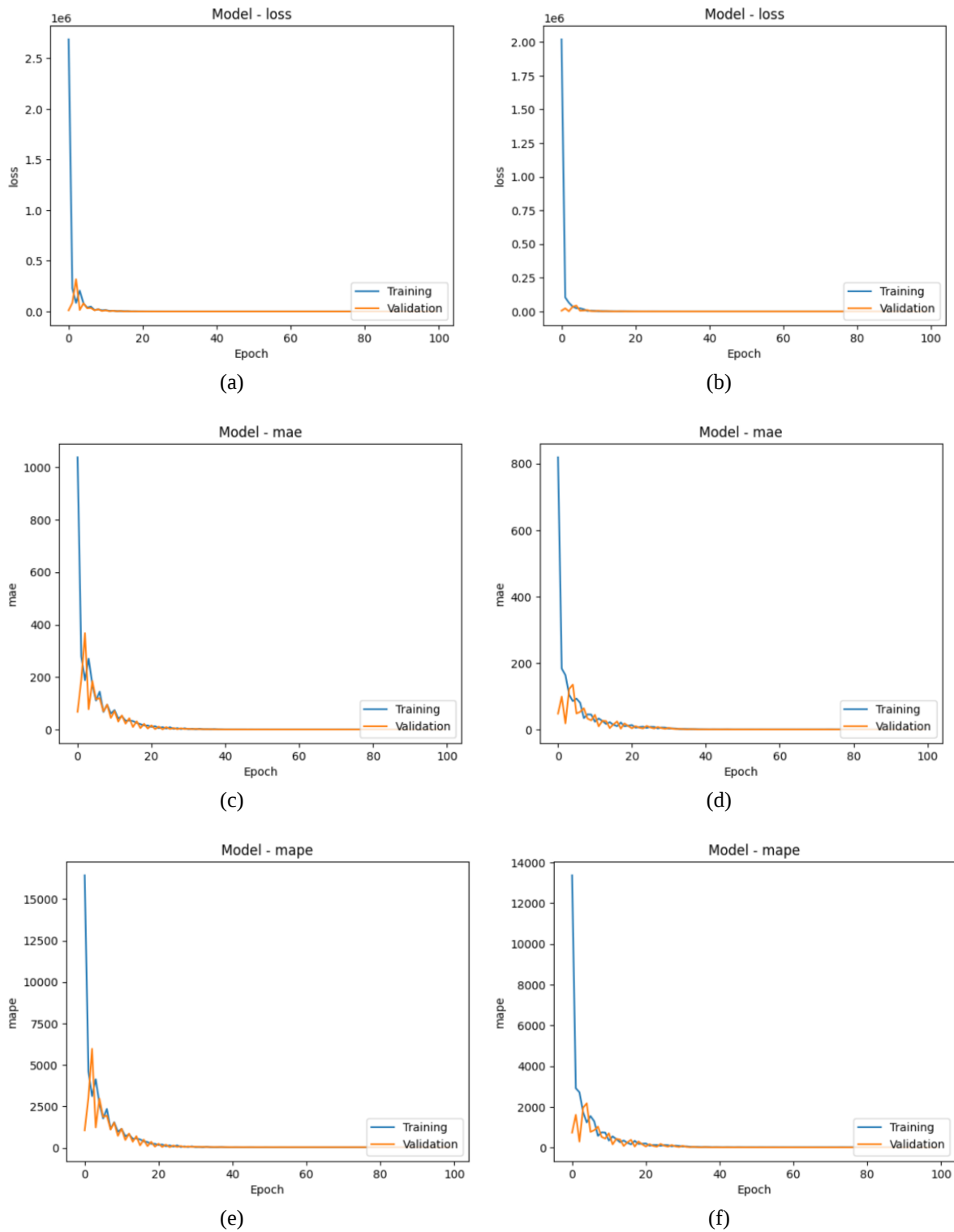


Figure 2. Training and testing process of (a) loss (MSE) value for 5 hidden layers, (b) loss (MSE) value for 6 hidden layers, (c) MAE for 5 hidden layers, (d) MAE for 6 hidden layers, (e) MAPE for 5 hidden layers, and (f) MAPE for 6 hidden layers

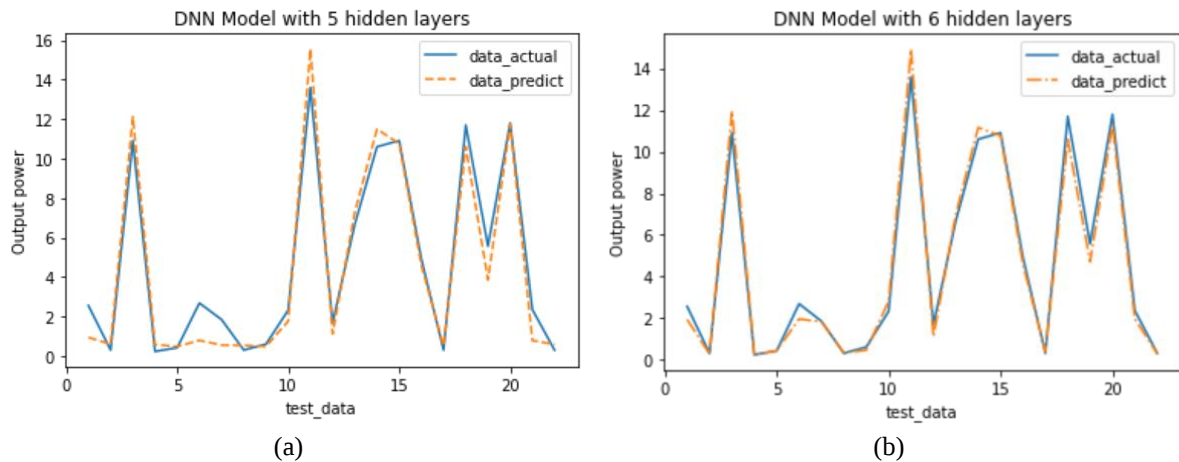


Figure 3. Comparison between actual data with predicted data for both models of (a) 5 hidden layers and (b) 6 hidden layers

4. CONCLUSION

The main goal of the current study was to optimize the power output of a dual-axis solar tracker. These experiments confirmed that a DNN model was successfully trained with hidden layer variations. The current data highlight the importance of the number of hidden layers. The accuracy of DNN with 6 hidden layers have better model performance in the testing process with a MAPE value of 12.328%, MSE of 0.332, and MAE 0.425 compared to DNN with 5 hidden layers. This work contributes to the existing solar tracker power output forecasting knowledge by providing a predictive model that leverages historical data. By optimizing power output predictions, this research could support the development of more efficient and cost-effective solar tracking systems. This, in turn, can encourage wider adoption of solar energy as a more reliable energy source. The model's performance may vary based on geographical location, sun path, and environmental factors not included in the training data. Testing the model in diverse locations could reveal limitations in generalizability.

FUNDING INFORMATION

The authors are grateful to the University of Lampung for providing financial support for the implementation of this study through the BLU Unila study grant.

AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Humairoh Ratu Ayu	✓	✓	✓	✓	✓			✓	✓	✓		✓	✓	✓
Rifki Mohamad		✓				✓	✓	✓		✓	✓			
Kurniawansyah														
Aqua Risma Diansari			✓	✓	✓		✓			✓	✓		✓	

C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [H. R. A.], upon reasonable request.

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